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Mean-variance investment strategy applied in emerging financial markets: Evidence from the Colombian stock market

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Abstract

In any investment, an analysis of the expected return and the assumed risk constitutes a fundamental step. Investing in financial assets is no exception. Since the portfolio selection theory was proposed by Markowitz in 1952, this methodology has become the benchmark in portfolio management. However, it is not always possible to apply it, especially when investing in emerging financial markets, which are characterised by a scant variety of available stocks and very low liquidity. In this paper, using the Colombian case, we will examine the challenges found by investors who want to create a portfolio using only stocks listed on a scarcely developed stock market.

JEL classification: G11; G12

Keywords: Diversification; Efficient frontier; Mean-variance; Profitability; Risk.

1. Introduction

The creation and management of investment portfolios is a major challenge in the financial arena. Indeed, many agents such as individual investors (Jacobs, Müller, & Weber, 2014) and pension funds or life insurance companies (Jablonskienė, 2013) seek to efficiently manage their investment portfolios instead of using other alternatives such as passive management (García, Guijarro, & Moya, 2013). Furthermore, alongside the traditional variables of risk and return, investors sometimes include other criteria in the selection of values as ethical criteria (Belghitar, Clark, & Deshmukh, 2014; Slapikaite & Tamosiuniene, 2013).

Modern portfolio theory was first introduced by Markowitz (1952) and later developed by Sharpe (1964). Modern portfolio theory establishes an investment framework for the selection and construction of portfolios based on maximising expected return and simultaneously minimising investment risk.

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Since its publication, the mean-variance portfolio selection model has been a fundamental theoretical reference in portfolio selection, leading to multiple developments and referrals.

Researchers, applying neural networks, have further analysed some problems in portfolio building, because neural networks can incorporate uncertainty related to stock returns in the models (Nazemi, Abbasi, & Omidi, 2015). This methodology can also improve the algorithm in the selection of stocks, generating a previous selection of the inputs to be used in models (Chen, Huang, Hong, & Chang, 2015).

Another problem studied is rebalancing the portfolio. Becker, Gürtler, & Hibbeln, 2013 analyse the effects of portfolio rebalancing with and without restrictions on the weights of stocks included in the portfolio.

Other studies incorporate new variables into the model. For example, Xia, Min, & Deng, 2015 include the consensus temporary earnings forecasting (CTEF) variable that is nothing more than a prediction of the different types of earnings in the market (e.g. one-/two-year forecasts of earning per stock).

Using algorithms such as particle swarm optimisation (PSO) and multi-objective particle swarm optimisers (MOPSOs) makes it possible to build multi-objective models. Mushakhian and Abbas (2015) apply these algorithms to the problem of selecting stocks that incorporate transaction costs.

Support vector machines (SVMs) can also be applied in selecting the assets to be included in the portfolio. SVMs select stocks that are more profitable (Barak & Modarres, 2015; Loukeris & Eleftheriadis, 2015), with the ability to extract complex and relevant information from accounting statements to help in the selection process (Hsu, 2014).

Other studies examine how to build index tracking models as efficiently as possible, avoiding high transaction costs (Chen & Kwon, 2012; Edirisinghe, 2013; García, Guijarro, & Moya, 2011).

The remainder of the paper is structured as follows: in the section following this introduction, the mean-variance model by Markowitz is presented; Section 2 is devoted to a description of the database of stocks listed in the Colombian stock market. In Section 3, Markowitz's model is applied and the main results are described. Finally, the last section draws conclusions.

2. Methodology

The expected return from a portfolio is the weighted average of the expected returns of individual stocks, which are frequently calculated using the historical behaviour of returns, and is calculated by the expression formed by the following components:

$$\mathrm{E}\left(R_p\right) = \sum_{i=1}^{n} \mathrm{w}_i E\left(R_i\right) \tag{1}$$

$$\sum_{i=1}^{n} w_i = 100\% \tag{2}$$

where:

$\mathrm{E}(R_p) =$ Expected return on the portfolio
$n =$ Number of stocks included in the portfolio
$w_i =$ Weighting of the stock "i" in the portfolio.
$E(R_i) =$ Expected return of the stock "i"

Risk can be defined as the possibility that the actual performance of an investment differs from what is expected.

The overall risk of a stock can be divided into two basic components: systematic risk (also called non-diversifiable risk, market risk or common risk) and unsystematic risk (also called diversifiable risk, specific risk or idiosyncratic risk). Portfolio selection theory assumes that these two types of risk are common to all portfolios. The risk of a diversified portfolio, measured by the standard deviation of performance, is:

$$\sigma^2{}_p = \sum_{i=1}^{n} . \sum_{j=1}^{n} w_i w_j \sigma_{ij} \tag{3}$$

$$\sigma_p = \sqrt{\sigma^2{}_p} \tag{4}$$

where:

$\sigma_p^2 =$ Variance of the portfolio
$\sigma_p =$ Risk of the portfolio
$w_i =$ Weighting of stock i
$w_j =$ Weighting of stock j
$\sigma_{ij} =$ Covariance between stock i and j

There are two approaches to selecting the stocks to be included in a portfolio. The first strategy maximises the return for a given risk and the second aims to generate a portfolio with the minimum possible variance for a given return.

- A portfolio's maximum return given a desired risk level:

$$\text{Max } E(R_p) = \sum_{i=1}^{n} w_i R_i \tag{7}$$

Subject to:

$$(1)\ \sigma_i^2 = \sum_{i=1}^{n} \cdot \sum_{j=1}^{n} w_i w_j \sigma_{ij} \tag{8}$$

Restricting portfolio risk: applying 7 and 8, the profitability of the portfolio will be maximised for a given level of risk.

$$(2)\ \sum_{i=1}^{n} w_i = 100\% \tag{9}$$

Budget constraint: the total investment amount available must be invested.

$$(3)\ w_i \geq 0$$

Restriction sign: this restriction indicates that no short positions are allowed.

$$(4)\ w_i \leq 40\%$$

It is not permitted to invest more than 40% of the amount available for investment in a single stock. The aim of this restriction is to avoid high concentration of investment in a single stock and diversify risk to other stocks.

- Portfolio of minimum variance given a desired level of profitability:

$$\text{Min } \sigma_i^2 = \sum_{i=1}^{n} \cdot \sum_{j=1}^{n} w_i w_j \sigma_{ij} \tag{10}$$

Subject to:

$$(1)\ E(R_p) = \sum_{i=1}^{n} w_i R_i \tag{11}$$

Applying 10 and 11, the risk of the portfolio will be minimised for a defined level of return.

$$(2)\ \sum_{i=1}^{n} w_i = 100\% \tag{12}$$

Budget constraint: the total investment amount available must be invested.

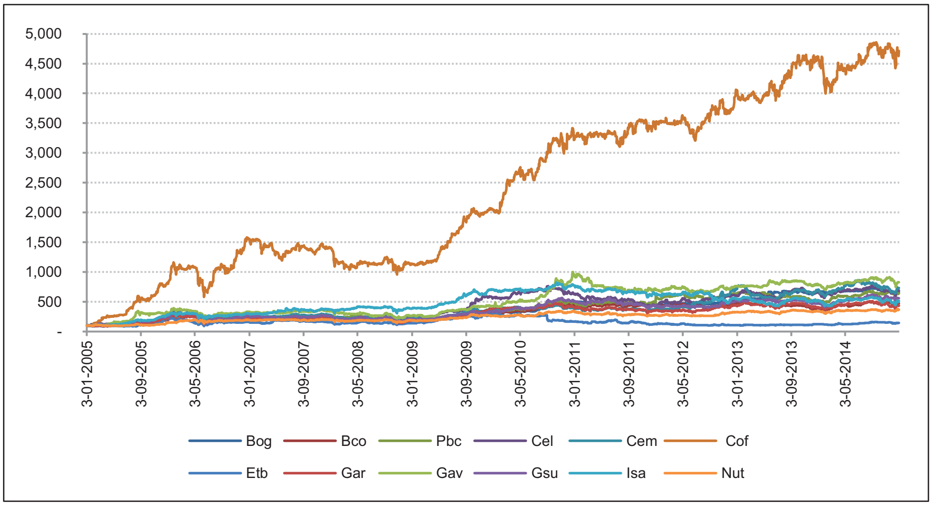
$$(3)\ w_i \geq 0$$

Restriction sign: this indicates that sales are not allowed in short.

Later, in the second part of the article, a new restriction will be included:

$$(4)\ w_i \leq 40\%$$

It is not permitted to invest more than 40% of the amount available for investment in a single stock. The aim of this restriction is to avoid the high concentration of investment in a single stock and diversify risk to other stocks.



Source: The authors

Fig. 1. Price performance of selected stocks.

3. Database

The aim of this paper is to apply the mean-variance model in the Colombian stock market, in order to create an investment portfolio with an optimum composition of stocks that obtain the maximum return for the lowest risk.

The Markowitz model is applied using daily closing prices for the period from January 2005 to December 2014. Closing prices have been collected for the following 12 companies: Banco de Bogotá SA (Bog), Bancolombia SA (Bco, Pbc), Celsia SA E.S.P. (Cel), Cementos Argos SA (Cem), Corporación Financiera Colombiana SA (Cof), ETB SA (Etb), Argos Group SA (Gar), Grupo Aval SA (Gav), Grupo Sura S.A. (Gsu) Interconexión Eléctrica SA (Isa) and Grupo Nutresa SA(Nut).

Of the 12 companies, six are in the financial sector (Bog, Bco, Pbc, Cof, Gav and Gsu), two belong to the energy sector (Cel and Isa), and the remaining four consist of a company in the cement industry (Cem), one in the telecommunications sector (Etb),one in the food sector (Nut), and a holding company with investments in cement, energy, urban and real-estate development, and ports (Gsu).

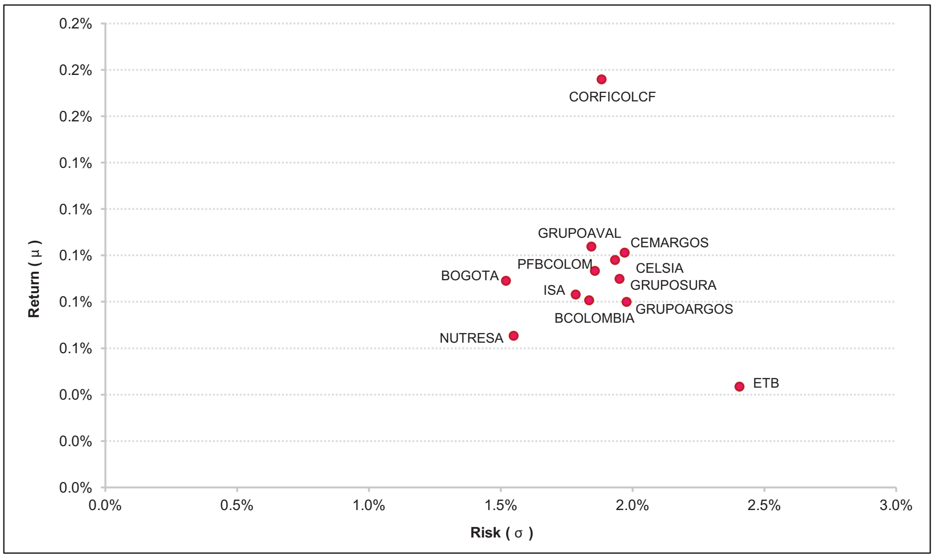
These 12 companies are the only ones listed on the Colombian stock exchange for which enough information is available for the period examined. The main problem with most of the companies not included in this study is that they do not have enough liquidity and their shares are not traded at all for periods that can last for several days, and even weeks. When shares are traded again, prices can significantly differ from those of the last trading period, showing very high volatility.

Fig. 1 shows the evolution of the main and more liquid stocks in the Colombian market. It can be observed that Corporación Financiera Colombiana (Cof) stands out above the other assets in terms of the price reached and its slope. The other stocks present a much more similar price evolution.

Fig. 2 compares the risk of each stock with its return, creating a chart of dominances in which one company dominates another when it has a higher return and lower risk. It becomes obvious that Corporación Financiera Colombiana (Cof) obtains the highest return among the companies in the sample– far more than the other stocks. Furthermore, Corporación Financiera Colombiana (Cof) has a lower level of risk than most of the other companies, thus dominating them in the mean-variance plane. This means that in the creation of a minimum-variance portfolio with high profitability requirements, the most dominant company– which is without doubt Corporación Financiera Colombiana (Cof)– will have the highest weighting in the portfolio.

4. Results

Applying the mean-variance model, the minimum-variance portfolio at a desired level of profitability is calculated.



Source: The authors

Fig. 2. Chart dominance of Colombian stocks.

Table 1
Minimum-variance portfolio.

Weight							σp	E [Rp]
Bog	Pbc	Cof	Etb	Gav	Isa	Nut		
32.05%	10.81%	7.13%	8.58%	7.66%	7.81%	25.96%	1.204%	0.086%

Source: The authors.

Table 1 shows the composition of the minimum-variance portfolio. This portfolio has an expected daily return of 0.086% and a variance of 1.204%. The firm Banco de Bogotá (Bog) has the highest weight (32.05%) in the minimum-variance portfolio because it is the least risky among the 12 stocks selected, followed by Nutresa.

As shown in Table 2, in the portfolio of maximum profitability, only Corporación Financiera Colombiana (Cof) is included. This is logical because this is the stock with the highest expected return among all the stocks.

Table 2 shows the composition of portfolios along the efficient frontier line– that is, combinations of stocks that offer the highest return for a given level of risk. The efficient frontier line is presented in Fig. 3 and has been drawn using 17 points. In other words, 17 different portfolios have been generated using the 12 available stocks and changing their weightings.

The first portfolio in Table 2 shows the composition of the minimum-variance portfolio. From the 12 companies, only seven are used to generate this portfolio. To createportfolios 5 and 6, only six companies are used, and this number is reduced to just four companies for portfolio 7. For portfolios 11 to 16, only Banco de Bogotá (Bog), Corporación Financiera Colombiana (Cof) and Grupo Aval (Gav) are included. Finally, portfolio 17 is composed solely of the shares of Corporación Financiera Colombiana (Cof).

For a conservative investor, the minimum-variance portfolio is a good choice. However, according to Markowitz, rational selection by investors and risk aversion lead them to seek different options for a portfolio geared towards generating good returns at a given level of risk, and create so-called indifference curves throughout the efficient frontier.

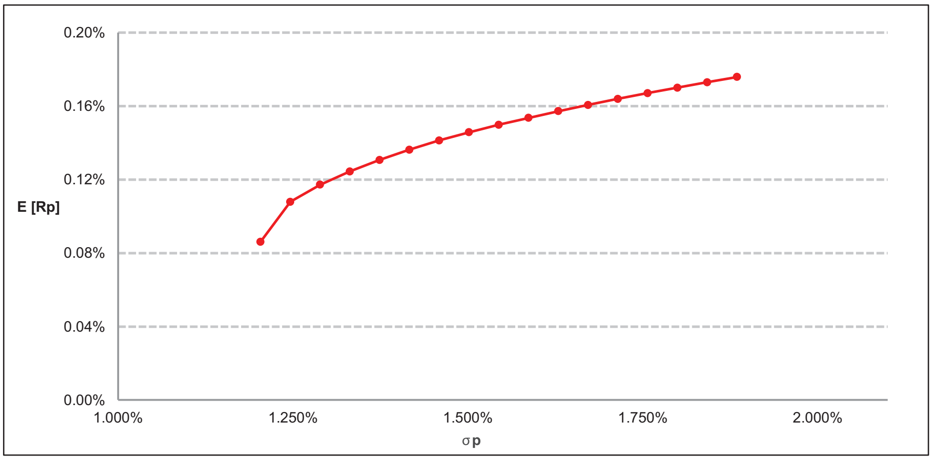
It is worth mentioning that an investor who wants to purchase stocks in the Colombian stock market can maximise profitability by investing in any of the portfolios located on the efficient frontier line, depending on the level of risk he or she wants to assume.

The results provide evidence that the Colombian stock market is very narrow, with only a few liquid securities, and is dominated by a single stock– which clearly hinders the diversification of risk in constructing minimum-variance portfolios. If an investor wants to achieve higher levels of profitability, this stock will have greater weight in the

Table 2
Efficient portfolio composition.

	Weight Bog (%)	Pbc (%)	Cel (%)	Cof (%)	Etb (%)	Gav (%)	Isa (%)	Nut (%)	σp (%)	E [Rp] (%)
1	32.05	10.81	0.00	7.13	8.58	7.66	7.81	25.96	1.204	0.086
2	30.29	10.20	0.00	26.42	3.88	9.20	4.15	15.86	1.246	0.108
3	29.47	9.84	0.14	34.59	1.69	9.78	2.92	11.56	1.289	0.117
4	28.79	9.30	1.47	40.81	0.62	10.22	2.19	6.60	1.331	0.124
5	28.05	9.24	0.66	46.96	0.00	10.74	0.00	4.35	1.374	0.131
6	26.59	8.42	0.58	52.51	0.00	10.79	0.00	1.10	1.417	0.136
7	24.65	6.64	0.00	58.14	0.00	10.57	0.00	0.00	1.459	0.141
8	21.82	4.92	0.00	63.45	0.00	9.81	0.00	0.00	1.502	0.146%
9	19.30	3.12	0.00	68.32	0.00	9.26	0.00	0.00	1.544	0.150
10	16.90	1.52%	0.00	72.88	0.00	8.71	0.00	0.00	1.587	0.154
11	14.68	0.00	0.00	77.20	0.00	8.11	0.00	0.00	1.629%	0.157
12	11.50	0.00	0.00	81.30	0.00	7.20	0.00	0.00	1.672	0.161
13	8.50	0.00	0.00	85.21	0.00	6.28	0.00	0.00	1.715	0.164
14	5.59	0.00	0.00	88.96	0.00	5.45	0.00	0.00	1.757	0.167
15	2.75	0.00	0.00	92.58	0.00	4.66	0.00	0.00	1.800	0.170
16	0.12	0.00	0.00	96.12	0.00	3.77	0.00	0.00	1.842	0.173
17	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	1.885	0.176

Efficient portfolios = 17.
Source: The authors.



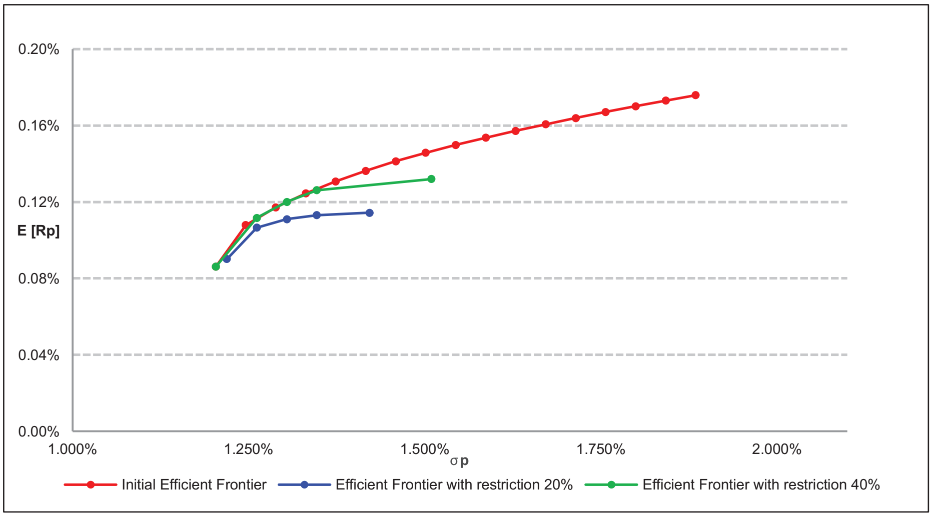
Source: The authors

Fig. 3. Line of efficient frontier composed of Colombian stocks.

portfolio, considerably increasing the risk. We have therefore considered the need to build portfolios by adding a restriction to the Markowitz model, preventing investment in more than a certain percentage in a stock.

The initial restriction we impose is that no more than 20% of the available funds can be invested in a single stock. In a second step, this is increased to 40%. Logically, these restrictions limit the possibilities for constructing portfolios for certain higher levels of profitability. In fact, as shown in Table 2 (portfolios without restriction), the portfolio with the highest profitability consists of a single stock. This means that there is no diversification at all, so the portfolio risk and its profitability will be equal to those of the stock. If investment of 100% of the available amount in a single stock is not permitted, this high a return cannot be achieved.

Fig. 4 presents the three efficient frontiers (the initial one, and those with restrictions of 20% and 40%). It can be observed that the minimum-variance portfolio is very similar for the three borders indicated. Likewise, it confirms that Banco de Bogotá (Bog), as the company with the lowest risk, has the highest investment weighting in each of the portfolios.



Source: The authors

Fig. 4. Efficient frontiers.

Table 3
Efficient portfolio composition with a restriction of 20%.

	Weight Bog (%)	Pbc (%)	Cel (%)	Cem (%)	Cof (%)	Etb (%)	Gav (%)	Isa (%)	Nut (%)	σp (%)	E [Rp] (%)
1	20.00	14.11	2.12	0.00	9.72	9.89	13.05	11.11	20.00	1.219	0.090
2	20.00	14.45	5.68	2.52	20.00	0.76	17.62	6.00	12.99	1.262	0.107
3	20.00	16.46	9.91	7.30	20.00	0.00	20.00	4.11	2.22%	1.304	0.111
4	17.37	11.62	13.01	18.00	20.00	0.00	20.00	0.00	0.00	1.347	0.113
5	0.00	20.00	20.00	20.00	20.00	0.00	20.00	0.00	0.00	1.422	0.114

Efficient portfolios = 5.
Source: The authors.

Table 4
Efficient portfolio composition with a restriction of 40%.

	Weight Bog (%)	Pbc (%)	Cel (%)	Cem (%)	Cof (%)	Etb (%)	Gav (%)	Isa (%)	Nut (%)	σp (%)	E [Rp] (%)
1	32.07	10.84	0.00	0.00	7.05	8.57	7.74	7.73	26.01	1.204	0.086
2	29.92	10.06	0.05	0.00	29.73	3.04	9.51	3.61	14.08	1.262	0.112
3	29.32	9.85	0.05	0.00	37.13	1.17	9.97	2.41	10.12	1.304	0.120
4	29.29	11.45	0.05	2.47	40.00	0.00	14.29	1.00	1.45	1.347	0.126
5	0.00	0.00	0.00	20.00	40.00	0.00	40.00	0.00	0.00	1.510	0.132

Efficient portfolios = 5.
Source: The authors.

However, when analysing the portfolios of maximum performance for each of the efficient frontiers, major differences can be observed. Moreover, it becomes obvious that in order to slightly increase the return on a portfolio, a large rise in risk must be assumed. (Tables 3 and 4).

Given the high level of dominance of Corporación Financiera Colombiana (Cof) over the other stocks, with the restrictions imposed it is undoubtedly difficult to build portfolios that obtain the maximum possible profitability.

The research undertaken makes clear the difficulties faced by Colombian investors who want to apply the mean-variance model in their domestic stock market. In order to solve these problems, one option could be to broaden the investment horizon towards other Latin American markets.

5. Conclusions

This paper applies the mean-variance model developed by Markowitz to the Colombian stock market in the period between January 2005 and December 2014.

The research undertaken highlights the difficulties faced by Colombian investors in implementing portfolio theory, given the characteristics of the country's stock market. The liquidity of stocks is a major problem. In fact, only 12 companies present complete information about stock prices for the selected period. This lack of information and available companies for building a portfolio has a very important impact on the portfolios that can be created under the model. Moreover, additional restrictions in the model to limit the maximum investment percentage to be allocated to a stock have a large influence on the composition of the final portfolio and its levels of risk and return.

To solve the problems of low liquidity and a lack of investment alternatives on the Colombian stock exchange, the country's investors need to look abroad to widen the range of companies to include in their portfolios. A natural step is to look at those companies listed on Latin American stock markets. For this reason, further research should be carried out to analyse the potential benefits of expanding one's investment horizon to other stock markets in the region to create pan-American portfolios.

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